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Auction Based Mechanisms for Electronic Procurement

T. S. Chandrashekar, Y. Narahari, Charles H. Rosa, Devadatta Kulkarni, and Jeffrey D. Tew

***Abstract*— This article reviews recent research and current art in the area of auction based mechanisms for electronic procurement. These mechanisms are becoming increasingly relevant in modern day e-procurement systems since they enable a promising way of automating negotiations with suppliers and achieving the ideal goals of procurement efficiency, cost minimization, truthful bidding, and agent based deployment. The survey categorizes the mechanisms into three classes: (1) multi-unit auctions for a single homogeneous type of item; (2) multi-attribute auctions where the procurement decisions transcend cost considerations alone, to take into account lead times, logistics costs, and other important attributes; and (3) combinatorial procurement auctions where the buyer strategically bundles up the buying requirements and the suppliers bid for subsets of these bundles. In all the three cases, the winner determination problem and the determination of payments turn out to be interesting, but challenging combinatorial optimization problems. In our review, we present mathematical formulation of representative problems under each category, bring out the challenge involved in solving the problems, and indicate active research topics. We also present two successful case studies of electronic procurement from the literature.**

***Index Terms*— Procurement, decentralized optimization, game theory, negotiations, auctions, multi-attribute auctions, combinatorial auctions, volume discount auctions, truthful bidding, set covering problem, NP-hard problems, heuristics, approximation algorithms.**

ACRONYMS

ICT	Information and Communication Technologies
RFQ	Request for Quote
LP	Linear Program
IP	Integer Program
MIP	Mixed Integer Program
MILP	Mixed Integer Linear Program
GP	Goal Programming
CA	Combinatorial Auction
GVA	Generalized Vickrey Auction
VCG	Vickrey-Clarke-Groves (mechanism)
NP	Non-Deterministic Polynomial Time
FPTAS	Fully Polynomial Time Approximation Scheme
MAUT	Multi-Attribute Utility Theory
MCDA	Multi-Criteria Decision Analysis
IRDA	Iterative Reverse Dutch Auction

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I. INTRODUCTION

THE purchasing function and the associated procurement processes in organizations, large and small, have traditionally been an important area of operations affecting business performance. Recent trends in the business environment suggest that their importance is being both reinforced through the emergence of global supply chains, and amplified by the growing incidence of outsourcing in many industrial sectors. Simultaneously, the procurement function itself has undergone much transformation. In one large global firm that the authors have worked with, decentralized, factored purchasing processes have given way to uniform, centralized purchasing practices, with world-wide purchasing decisions co-ordinated by a single centralized organization. These changes can, in part, be attributed to the influence that information and communication technologies (ICT's) have had in reshaping procurement processes both within and between organizations.

The procurement process itself may be hierarchically decomposed and a first level decomposition yields four distinct stages: *supplier search and analysis, supplier selection stage, automated transactional stage, and supply chain planning and control.* While many aspects of procurement, in each of the four stages, have benefited from the application of ICT's and decision technologies, *negotiations*, which form a crucial part of the supplier selection stage have so far relied on human based processes with little technological support. This, however is poised for change.

Negotiation is the key decision making approach used to reach a consensus whenever a person, organization, or any other entity cannot achieve its goals unilaterally [1]. In the procurement context, negotiations help resolve situations with *conflicts of interest* between buyers and sellers. Given this context, *negotiation* has been on the research agenda of many diverse disciplines including anthropology, psychology and sociology, political sciences, law and applied mathematics [2]. Now, with the establishment of the Internet as an important infrastructure component affecting the design of business processes, there is a fresh new perspective to the research agenda on negotiations. While earlier research in negotiations was based on the results of studies in economic and social sciences, the latest perspective has shown that computational models and systems can significantly influence the construction of negotiation techniques, models, and procedures.

The increased computing and networking power enabled through the Internet has provided a new flexibility in designing negotiations while at the same time the findings in computer science and information systems have fed back into models

and procedures of negotiation. These studies have contributed to the development of negotiation support systems, software agents for negotiation, and on-line electronic platforms for bidding and auctioning. Electronic auctions available in many on-line marketplaces provide the framework for automated negotiations in retail e-commerce settings. The success of on-line auction sites like www.ebay.com, www.freemarkets.com, and www.onsale.com and the growth of private electronic marketplaces are opening up new vistas for automation of negotiation processes with the promise of higher levels of efficiency and effectiveness, and more importantly, a higher quality and faster emergence of agreements in complex industrial procurement scenarios. Auctions have emerged as an important Internet-based tool for many B2B applications. General Electric has adopted online auctions for most of its procurement operations, conducting more than 6 billion in online auctions in 2000 [3], which led to the *Internet Week* magazine awarding the title "E-Business of the Year 2000." Numerous major companies have either used or in the process of using auction-based methods or Internet-based automated negotiations for their procurement operations. There are many published case studies of successful deployment of e-auctions in procurement, for example, see [4], [5], [6], [7].

In this paper we review recent research and current art related to the design of auction based procurement mechanisms in order to:

- understand the variety of negotiation models developed to support different procurement scenarios, and
- bring together the key technical and business requirements in the implementation of auction based protocols for negotiation and supplier selection.

A. *Outline of the Paper*

In Section II, we outline a few industrial procurement scenarios to illustrate the diversity that we have observed in practice and to motivate the subsequent review of the design and development of negotiation protocols based upon auction theoretic models. We also briefly summarize some of the approaches, complementary to auctions, that have been taken to provide a sense of completeness. In Section III we provide a brief discussion of the key technical criteria in the design of auction based models for electronic procurement. Section IV describes models for single item, multi-unit procurement scenarios with transfer price as the only attribute for decision making. In Section V, we describe single item, multi-unit, multi attribute models. In Section VI we discuss multi-item (Combinatorial) procurement models with transfer price as the only criterion. In Section VII, we discuss industrial cases of where auction based procurement mechanisms have been implemented. Finally in Section VIII, we conclude the review and provide pointers to some of the issues with the current genre of models and a brief discussion of directions for future work.

The paper focuses on *procurement auctions* and is therefore not to be treated as a survey on *auctions* in general. There are excellent surveys on general auctions; for example, see [8], [9], [10], [11], [12], [13]. For a survey of combinatorial auctions, see [14], [15], [16], [17]. The books by Milgrom [18] and Vijay Krishna [19] are excellent treatises on general auction theory. There is a popular on-line book on auctions by Klemperer [20]. There is a very comprehensive recent book on combinatorial auctions by Cramton, Shoham, and Steinberg [21].

In putting together this article, we have benefited immensely from the discussions in the following articles: [8], [12], [17], [14], [15], [16], [4], [6], [22], [23], [24], [25].

II. AUTOMATED NEGOTIATIONS IN PROCUREMENT

A. *Negotiation Scenarios*

In this section we describe a few procurement situations drawn from real life scenarios that we have studied. These scenarios progressively illustrate the range of complexity in procurement situations: from buying the proverbial *pin (very simple) to a plane (very complex).*

1) Scenario A: Buying a Cutting Tool: A Purchase Request (PR) to buy a specific cutting tool is generated by a user department, such as production. This request is communicated to a central buying department called Purchasing. The buyer responsible for this category of items acknowledges the request. If the item is in one of the standard price lists of vendors already supplying to the organization and a blanket order already exists then a spot buy order is sent to the supplier. Otherwise a request for quote (RFQ) is prepared by the buyer and sent to a selection of suppliers who respond with quotes. These quotes are analyzed and a sourcing recommendation is made based on the prices that are quoted. This is a very simple buying situation where the decision to buy a single item is made on the basis of a single attribute - price per unit.

Now, consider the same situation as above except that multiple units of the item are to be bought. The suppliers are now able to exploit economies of scale and hence provide bids with volume discounts thereby introducing one level of complexity in the buyer's winner determination problem.

In the scenario above, very often it is observed that the same tool is required by many plants across a geographical region or across all plants world-wide. In such cases the buyer creates a blanket order which can be used by all the plants. The blanket order specifies a single price and the delivery point is the nearest pickup location operated by third party logistics providers on behalf of the manufacturer. Clearly in this case the sourcing decision involves a greater degree of complexity since the total cost of procurement - the per unit cost of the item and the shipment cost, is to be optimized by the buyer.

2) Scenario B: Buying a Family of Cutting Tools: Here, we discuss an extension to the previous scenario. Purchase requests may be raised by user departments across the organization for many types of cutting tools. These requests are processed by a single buyer responsible for the procurement of cutting tools. The requests are aggregated and in some cases bundled and an RFQ is generated. The suppliers respond with bids for bundles which provide volume discounts as well as point prices. The buyer has to make a decision of allocating the orders so as to minimize his total cost of procurement as well as restrict the number of suppliers who receive the

orders so as to reduce management overhead. The decision problem in this case can be challenging, and in some cases if the number of suppliers is large then the computations involved can overwhelm the buyer.

3) Scenario C: Buying a Machine Tool: While it may be possible to buy cutting tools off-the-shelf by negotiating along only one dimension - price, buying a machine tool for a specific machining requirement depends on many attributes. These may include at least the following: quality of machine tool, lead time to manufacture and deliver, availability of spares, maintenance spares to be held in inventory, etc. It may be possible to attach a monetary value to some or all of the attributes that influence the purchase decision. In some cases, additional features and options could be purchased as add-on components to the basic machine tool from some or all of the suppliers. Grappling with such multi-attribute decision problems is the *raison d'etre* of purchasing organizations.

B. Approaches to Automated Negotiation Systems

Based on the procurement scenarios depicted in the previous section, a negotiation can be described as an iterative communication and decision making process between two or more agents (parties, their representatives or software agents) who cannot achieve their objectives through unilateral actions, and hence engage in exchanging information comprising offers, counter-offers, and arguments, thereby searching for a consensus which is a compromise decision [2]. The scenarios also indicate the spectrum of decision making processes: from those based on value alone to those where the attributes for decision making keep evolving and hence the possible solution sets may themselves keep changing as more information is collected. Kersten *et al* [26] capture this spectrum of possibilities succinctly by classifying negotiations into the integrative and distributive types. From this it is clear that in order to build systems for automated negotiations, it is important to understand the requirements for the entire negotiation spectrum.

In this section we discuss three, not entirely disjoint, approaches - negotiation support systems, intelligent agents, and auctions as economic mechanisms, that have been proposed to automate the negotiation process in industrial procurement settings. We also identify points in the negotiation spectrum which each of the approaches target to automate.

1) Negotiation Support Systems: A Negotiation Support System (NSS) is a software program which is specifically oriented towards helping human negotiators make better decisions and represents a first step towards automated negotiations [27]. However these systems while requiring nearly constant human input leave the final decisions to human negotiators and hence are far from able to support automated negotiations on their own. Web based prototypes of negotiation support systems can be found at http://www.business.carleton.ca/inspire and http://www.business.carleton.ca/inter- neg/tools/inss/. These systems typically address the automation requirements for integrative negotiation scenarios but do not provide *intelligent* decision making capability.

2) Intelligent Agents: Intelligent software agents which participate in electronic marketplaces typically operating on principles of economic mechanism design have been proposed in [28] and [29]. These software agents, each with their own agenda, electronically negotiate with each other in an environment governed by rules. The *strategies* for negotiation may be explicitly and completely programmed into the agent or they could be *learning* agents. KASBAH [28], a marketplace for negotiating the purchase and sale of goods using software agents is an example of the former type. Here users specify the complete strategy for negotiations through a web based form and also retain control of the agent throughout its existence. On the other hand, BAZAAR [29] is another experimental system where negotiation is modeled as a sequential decision making task using Bayesian learning as the underlying mechanism. Genetic algorithms and genetic programming [30] are other approaches that have been suggested and used to enable learning by agents in negotiation and bargaining situations. These technologies essentially substitute the human element in negotiations with well defined ontologies covering products, messages, and decision rules. They therefore typically address the automation requirements of only the bidding process which when used in conjunction with the mechanisms within the marketplace infrastructure provide solutions for distributive negotiations.

3) Economic Mechanism Design and On-line Auctions: Economic mechanism design is concerned with the design of the *rules of interaction*, using the tools of economics and game theory, for economic transactions that will, in principle, yield some desired outcome. In the context of negotiations for procurement we require rules governing: (1) bidding for contracts, (2) the issues and attributes that will be considered to determine winner(s) of the contract, (3) determination of winning suppliers, and (4) the payments that will be made. English auctions, Dutch auctions, and sealed bid contracts are well understood, widely used economic mechanisms in the procurement context. Since the *rules of interaction* are well laid out, they have been a natural target for automation, and as a result have formed the core conceptual constructs on which on-line auctions, like those seen in ebay.com, onsale.com, freemarkets.com, etc., have been based. As we move automation from the distributive end of the negotiation spectrum to the integrative end, a number of technical concerns both from computational and economic perspectives need to be understood, and addressed through the proper design of auction mechanisms. We enumerate and briefly discuss the key criteria for the design of electronic auction mechanisms in the next section.

III. Issues in Electronic Auctions

As discussed in the previous section, auctions constitute a major class of economic mechanisms studied in microeconomics and game theory [19], [18]. Classical mechanism design literature has delineated several useful properties for mechanisms such as efficiency, individual rationality, and budget balance, and incentive compatibility. The challenge in automating these mechanisms is to ensure computational tractability while retaining the desirable properties.

In this section, we briefly discuss a few important issues in auctions in order to build the necessary background for the subsequent discussion on procurement mechanisms.

A. *Types of Auctions*

An Auction is a mechanism to allocate a set of goods to a set of bidders on the basis of the bids and asks. In a classical auction, the auctioneer wants to allocate a single item to a buyer among a group of bidders. There are four basic types of the classical auction prominently described in the literature [8], [9], [13], [10]: Open cry auction, Dutch auction, first price sealed bid auction, and second price sealed bid auction (also called the Vickrey auction). Auctions have evolved and grown far beyond these four types of mechanisms. Kalagnanam and Parkes [12] have suggested a framework for classifying auctions based on the requirements that need to be considered to set up an auction. These requirements fall into six categories [12].

(1) *Resources*: An auction involves a set of resources over which the negotiation is to be conducted. The resource could be a single item or multiple items, with a single or multiple units of each item. Another common consideration is the type of the item, i.e., is this a standard commodity or multi-attribute commodity. In the case of multi-attribute items, the agents might need to specify the non-price attributes and some utility/scoring function to trade-off across these attributes.

(2) *Market Structure*: An auction provides a mechanism for negotiation between buyers and sellers. In *forward auctions* a single seller sells resources to multiple buyers. In a *reverse auctions*, a single buyer attempts to source resources from multiple suppliers, as is common in procurement. Auctions with multiple buyers and sellers are called *double auctions* or *exchanges*, and these are commonly used for trading securities and financial instruments and increasingly within the supply chain. In this paper, our interest is in *reverse auctions* which we call in general as *procurement auctions*.

(3) *Preference Structure*: The preference structure of agents in an auction is important and impacts some of the other factors. The preferences define an agent's utility for different outcomes. For example, when negotiating over multiple units agents might indicate a decreasing marginal utility for additional units. An agent's preference structure is important when negotiation happens over attributes for an item, for designing scoring rules used to signal information.

(4) *Bid Structure*: The structure of the bids within the auction defines the flexibility with which agents can express their resource requirements. For a simple single unit, single item commodity, the bids required are simple statements of willingness to pay/accept. However, for a multi-unit identical items setting bids need to specify price and quantity. This introduces the possibility for allowing volume discounts, where a bid defines the price as a function of the quantity. With multiple items, bids may specify all-or-nothing, both with price on a basket of items. In addition, agents might wish to provide several alternative bids but restrict the choice of bids.

(5) *Matching Supply to Demand*: A key aspect of auction is matching supply to demand, also referred to as market clearing, or *winner determination*. The main choice here is whether to use *single-sourcing*, in which pairs of buyers and sellers are matched, or *multi-sourcing* in which multiple suppliers can be matched with a single buyer, or vice-versa. This form of matching influences the complexity of winner determination, and problems range the entire spectrum from simple sorting problems to NP-hard optimization problems.

(6) *Information Feedback*: An auction protocol may be a *direct* mechanism or *indirect* mechanism. In a direct mechanism such as a sealed bid auction, agents submit bids without receiving feedback, such as price signals, from the auction. In an indirect mechanism, such as an ascending-price auction, agents can adjust bids in response to information feedback from the auction. Feedback about the state of the auction is usually characterized by a *price signal* and a *provisional allocation*, and provides sufficient information about the bids of winning agents to enable an agent to redefine its bids. In complex settings, such as multi-item auctions with bundled bids, a direct mechanism can require an exponential number of bids to specify an agent's preference information, on a "as required basis". The focus in the design of indirect mechanism is to identify how much preference information is sufficient to achieve desired economic properties and how to implement informationally-efficient mechanisms. A related area of research is to provide compact bidding languages for direct mechanisms.

In this paper, our interest is in *procurement auctions* and we focus attention on three representative types of procurement auctions:

- Single item, single attribute procurement auctions (single unit or multi-unit) (Section IV)
- Single item, multi-attribute procurement auctions (Section V)
- Multi-item, single attribute procurement auctions (Section VI)

B. *Valuation Issues*

Asymmetry of information is a crucial element in any type of auction [8]. In procurement auctions, it is unreasonable to expect every bidder to possess the same amount of information. Also, there are bound to be differences among the valuations of an item or a set of items. With respect to bidders valuations, two extreme models which are possible are: *Independent-private-values model* and *common-value model* [8].

In the *independent-private-values-model* model, each bidder knows precisely how she values the item. She does not know the valuations of other bidders for this item but perceives any other bidder's valuation as a draw from a probability distribution. Also, she knows that the other bidders regard her own valuation as being drawn from a probability distribution. Formally, bidder i is associated with a probability distribution F_i from which she draws her valuation v_i. Bidder i alone knows about v_i and all other bidders only know the distribution F_i. The valuations of any pair of bidders are mutually

independent.

In the *common-value model*, the item has a single objective value but nobody knows its true value. The bidders, having access to different information sources, have different estimates of the item's valuation. If V is the item's true value (unobserved), each bidder bidder i, has a perceived value v_i which is an independent draw from a probability distribution $H(v_i|V)$. All the bidders know the distribution H.

The above two models represent two extreme models. Real-world procurement auctions will have features of both these models.

C. Properties Desired from an Auction

Solution Equilibrium: The solution of a mechanism is in equilibrium, if no agent wishes to change its bid, given the information that it has about other agents. Many types of equilibria can be computed given the assumptions about the preferences of agents (buyers and sellers), rationality, and information availability. They include: *Nash equilibrium, Bayesian Nash Equilibrium, dominant strategy equilibrium.* For a detailed discussion of these concepts, we refer the reader to [31].

Efficiency: A general criterion for evaluating a mechanism is *Pareto efficiency*, meaning that no agent could improve its allocation without making at least one other agent worse off. Another metric of efficiency is *allocative efficiency* which is achieved when the total utility of all the winners is maximized. When allocative efficiency is achieved, the resources or items are allocated to the agents who value them most.

Individual Rationality: A mechanism is individually rational if its allocations do not make any agent worse off than had the agent not participated in the mechanism. That is, every agent gains a non-negative utility by being a participant in the mechanism.

Budget Balance: : A mechanism is said to be *weakly* budget balanced if the the revenue to the auctioneer or the exchange is non-negative while it is said to be *strongly* budget balanced if this revenue is positive. Budget balance ensures that the auctioneer or the exchange does not make losses.

Incentive Compatibility: A mechanism is incentive compatible if the agents optimize their expected utilities by bidding their true valuations for the goods. This is a desirable feature because an agent's decision depends only on its local information and it gains no advantage in expending effort to model other agents' valuations. It is desired that truthful bidding by the agents should lead to a well defined equilbrium such as a dominant strategy equilbrium, in which case, the mechanism is said to be *strategy proof*.

Solution Stability: The solution of a mechanism is stable, if there is no subset of agents that could have done better, coming to an agreement outside the mechanism.

Revenue Maximization or Cost Minimization: In an auction where a seller is auctioning a set of items, the seller would like to maximize total revenue earned. On the other hand, in a procurement auction, the buyer would like to procure at minimum cost. Given the difficulty of finding equilibrium strategies, designing cost minimizing or revenue maximizing auctions is not easy.

Low Transaction Costs: The buyer and sellers would like to minimize the costs of participating in auctions. Delay in concluding the auction is also a transaction cost.

Fairness: This influences bidders willingness to participate in auctions. Winner determination algorithms, especially those based on heuristics, could lead to different sets of winners at different times. Since there could be multiple optimal solutions, different sets of winners could be produced by different specific exact algorithms used. Bidders who lose even though they could have won with a different algorithm could end up feeling unfairly treated.

Failure Freeness: Auction designs should work as intended under all but the most extreme conditions. Transparency is also important because (1) it simplifies bidders understanding of the situation and eases their decision making (2) increases their trust in the auction process by improving their ability to verify that the auction rules have indeed been followed.

D. Possibilities and Impossibilities

There is a rich body of results in mechanism design theory dealing with what combinations of properties are possible and what are not possible to be achieved by an economic mechanism such as auctions. We provide a few important examples.

- Hurwicz [32] showed that it is impossible to achieve allocative efficiency, weak budget balance, and individual rationality in a Bayesian Nash incentive compatible mechanism.
- According to Arrow [33], allocative efficiency and strong budget balance cannot be achieved in a dominant strategy equilibrium.
- Myerson and Satterthwaite [34] showed that no exchange (that is with multiple sellers and multiple buyers) can be efficient, budget balanced, and individual rational at the same time; this holds with or without incentive compatibility.
- It was shown by Myerson [35] that revenue maximization, individual rationality, and incentive compatibility can be achieved simultaneously.
- McAfee [36] showed that strategy proof double auctions are possible with weak budget balance.
- It has been shown that the generalized Vickrey auction [37] satisfies four properties simultaneously: allocative efficiency, individual rationality, weak budget balance, and strategy proofness.

The above results provide a glimpse of what is possible and what is impossible in the design of mechanisms. For more details on these results, refer to [17], [12], [19].

E. Incentive Issues

We now present some issues related to incentives, based on the discussion in the papers by McAfee and McMillan [8] and Pekec and Rothkopf [15]. Informally, a procurement mechanism describes any process that takes as inputs the bids of the sellers and determines which bidders will be allocated the item(s) and how much payment is received by

the winning bidders. A mechanism is incentive compatible if the mechanism is structured in a way that each bidder finds it "optimal" in some sense to report his valuation truthfully. An incentive compatible mechanism induces truth revelation by the bidders by designing the payoff structure in a way that it is in the best interests of the bidders to bid truthfully. The second price sealed bid auction or the Vickrey auction for a single unit of a single item has been shown to be incentive compatible [38]. The generalized Vickrey auction is an example of an incentive compatible combinatorial auction mechanism [39], [14]. VCG (Vickrey-Clarke-Groves) mechanisms [38], [40], [41], [17] provide a broader class of incentive compatible mechanisms. These mechanisms induce truth revelation by paying a surplus amount to each winning bidder, over and above his actual bid. This surplus which is called the *Vickrey Surplus* is actually the extent by which the total procurement cost is decreased due to the presence of this bidder (marginal contribution of the bidder to the total cost of procurement).

VCG mechanisms have very attractive properties. For example, the GVA mechanism already stated, is allocatively efficient, individual rational, weakly budget balanced, and incentive compatible. However these mechanisms are not commonly used for many reasons. The first reason is they are not revenue efficient because of the payment of Vickrey surpluses or Vickrey discounts. The second reason is the computation of Vickrey surpluses and Vickrey discounts involves solving as many NP-hard problems as the number of winning bidders. The third reason is it entails every bidder to submit bids for every combination of items. They are also subject to several kinds of manipulations and are unsustainable in realistic auction settings [15].

F. Computational Complexity Issues in Mechanism Design

In an economic mechanism where resource allocation is done based on decentralized information, computations are involved at two levels: first, at the agent level and secondly at the mechanism level. The complexity questions involved are briefly indicated below. For a more detailed discussion refer [17], [12].

Complexity at the Agent Level:

- *Strategic Complexity*: Must agents model other agents and solve game theoretic problems to compute an optimal strategy? For instance, in a sealed bid procurement contract scenario, sellers will need to not only take their valuation of the contracts into consideration but also the bidding behavior of their competitors. This requires sophisticated bidding capability.
- *Valuation Complexity*: How much computation is required to provide preference information within a mechanism? For instance, in a multi item procurement scenario where the items exhibit cost complementarities, estimating a bid for every possible permutation of the bundle of items is hard.

Complexity at the Mechanism Level:

- *Winner Determination Complexity*: How much computation is expected of the mechanism infrastructure to compute an outcome given the bid information of the agents.
- *Communication Complexity*: How much communication is required between agents and the mechanism to compute an outcome. For instance, in an English auction, where individual valuations are revealed progressively in an iterative manner, the communication costs could be high if the auction were conducted in a distributed manner over space and/or time.

G. Summary

In this section, we have discussed important issues in auctions: valuation issues, desirable properties of a mechanism, possibilities and impossibilities, incentive issues, and computational complexity aspects. These issues are extremely relevant for electronic procurement auctions. We will be alluding to a few important properties (allocative efficiency, cost minimization, incentive compatibility, and fairness) while discussing procurement mechanisms in subsequent sections. We will also touch upon complexity issues while discussing different procurement mechanisms.

IV. Single Item, Multi-Unit, Single Attribute Procurement Mechanisms

In this section, we discuss the modeling of the procurement of a single item with price as the only consideration for decision making under a variety of different business contexts. Specifically, we review: (1) auction mechanisms for a single unit of an item, (2) auctions for multiple units of a single item with volume discount bids, and (3) auction mechanisms for procuring multiple units of a single item for multiple manufacturing points taking into account logistics considerations.

A. Procurement Auctions for Single Unit of an Item

In many procurement scenarios, firms both private and public use the *sealed bid tender* process to decide the *winner* of the contract. The *winning* rule is generally a first price rule. This process is one of the four basic types of auction mechanisms - English Auction, Dutch Auction, First Price Sealed Bid auction, and the Second Price Sealed Bid (Vickrey) auction, that have been well studied in the economics literature. Excellent reviews of the various results in Auction Theory from an economics / game theoretic perspective are presented in [8], [10], [13], [8], and [42]. A computational perspective when auctions are to be automated over the Internet is provided in [43]. A detailed discussion of the results in auction theory is beyond the scope of this paper. Here, we merely summarize one key result - the *revenue equivalence theorem*, and comment upon the computational issues that arise when automated implementations of these auction mechanisms are used in a procurement context.

The *revenue equivalence theorem* [8], [19], [18] states that the English, Dutch, First price sealed bid and Vickrey auctions yield the same average utility (revenue) for the buyer when one item is being bought, under the following assumptions [8].

1) The bidders are risk neutral (their bids do not take into account any risk perceptions they might have)

2) The valuations of bidders follow the independent private values model
3) The bidders are symmetric (that is all of them draw their valuations from the same probability distribution)
4) Payments or prices depend only on bids

Although experimental research [11] does not support this game theoretic *hyper-rational* view of human agents, it may well be the model of choice for automated software based auction mechanisms [37]. However, when the four mechanisms are evaluated from a computational perspective, it is clear that the computational challenges are not equivalent. We summarize the differences below.

1) Computational Implications of the four Basic Auction Mechanisms: As indicated in the previous section, complexity can be analyzed at the level of the agent - strategic and valuation complexities, and the mechanism - winner determination and communication complexities.

Strategic Complexity: Clearly for an agent participating in a Vickrey auction, which is incentive compatible, the strategic complexity is reduced to just bidding one's true valuation without a consideration for the strategies that would be followed by other agents. However, agents in the English, Dutch, and first price sealed bid auctions require to base their bids not only on their private valuations but also condition them on the valuations of their competitors. This requires them to process additional information - the number of competitors, the probability distributions of their valuations, etc. which increases their computational overhead. The English auction has certain benefits relative to the Dutch and First Price Sealed auctions. In an English auction, if all bidders bid up to their true valuations, no single bidder can gain by unilaterally deviating from this *truthful* strategy.

Communication Complexity: The communication overhead, and hence the processing overhead, is clearly much higher in multi round mechanisms like the English and Dutch auctions as compared to single shot mechanisms such as the Vickrey and first price sealed bid mechanisms.

The winner determination and valuation complexities however are straightforward for all four mechanisms.

B. Volume Discount Auctions

In a procurement context when there is a single buyer and multiple sellers who wish to exploit scale economies a *volume discount auction* is conducted where suppliers provide bids as a function of the quantity that is being purchased [6], [44]. The winner determination problem for this type of auction mechanism is to select a set of winning bids, where for each bid we select a price and quantity so that the total quantity of the demand of the buyer is satisfied at minimum cost.

The winner determination for this type of an auction is fairly straightforward if there are no business constraints such as maximum/minimum number of units that are to be purchased from a supplier, minimum/maximum number of winning suppliers, etc. The computational problem is to simply find the supplier who offers the *best price* and buy the entire quantity from this seller. However, procurement problems in practice rarely occur without business constraints being present. See [12], [45] for a comprehensive tabulation of business constraints that are observed in practice. With the addition of business constraints, the winner determination problem becomes a mixed integer programming problem (MIP) [6], [46]. In the following subsection, we provide a mathematical formulation of the volume discount auction problem adapted from [44], [47] and discuss some of the computational issues that arise in determining the winning bids.

TABLE I
NOTATION FOR VOLUME DISCOUNT AUCTIONS

K	number of lots to be procured by buyer
k	index for the lots ($k = 1, \ldots, K$)
Q^k	quantity for lot k
N	number of suppliers
i	index for the suppliers ($n = 1, \ldots, N$)
B_i^k	supply curve (bid) from supplier i for lot k
M_i^k	number of price-quantity pairs in bid B_i^k
P_{ij}^k	unit price the supplier is willing to charge for lot k if the number of units bought from this supplier is within the interval $[Q_{ij,low}^k, Q_{ij,high}^k]$
x_{ij}^k	decision variable that takes value 1 iff the buyer buys a quantity in the range $[Q_{ij,low}^k, Q_{ij,high}^k]$
z_{ij}^k	a continuous variable that specifies the exact number of units of lot k bought

1) Mathematical formulation of volume discount auctions: The volume discount procurement auction is represented in the following way [44], [47]. Table 1 provides the notation.

- The buyer has K lots that s/he needs to procure, and requires a quantity $Q^k, k = 1, \ldots, K$ for each lot. Each lot may correspond to a different type of item, however the lots are independently processed in the auction. Suppliers submit separate bids for each lot. As such, this can be treated as K independent, single item, multi-unit auctions.
- The buyer identifies a list of potential suppliers $i = 1, \ldots, N$ who can bid in the auction.
- Each supplier responds with a bid composed of a supply curve (at most one for each lot). A supply curve from supplier i for lot k given by a bid B_i^k consists of a list of M_i^k price quantity pairs, $\{(P_{i1}^k, [Q_{i1,low}^k, Q_{i1,high}^k]), \ldots, (P_{i|M_i^k|}^k, [Q_{i|M_i^k|,low}^k, Q_{i|M_i^k|,high}^k]\}$. Each price-quantity pair $(P_{ij}^k, [Q_{ij,low}^k, Q_{ij,high}^k])$ specifies the price P_{ij}^k that the supplier is willing to charge per unit of the lot k if the number of units bought from this supplier is within the interval $[Q_{ij,low}^k, Q_{ij,high}^k]$. It is assumed that the quantity intervals within a single supply curve are all pairwise disjoint.

The MIP formulation is as follows:

- A decision variable x_{ij}^k is associated with each price-quantity pair $(P_{ij}^k, [Q_{ij,low}^k, Q_{ij,high}^k])$ for each bid B_i^k. This is a $0-1$ variable taking on the value 1 if we buy some number of units within the price range and 0 otherwise.
- A continuous variable z_{ij}^k is associated with each price-quantity pair, which specifies the exact number of units

of the lot that are purchased from the bid b_i^k within this price-quantity pair.

The formulation:

$$\min \sum_{k\in K}\sum_{i\in N}\sum_{j\in M_i^k} z_{ij}^k * P_{ij}^k + \sum_{k\in K}\sum_{i\in N}\sum_{j\in M_i^k} x_{ij}^k * C_{ij}^k \quad (1)$$

subject to:

$$z_{ij}^k - (Q_{ij,high}^k - Q_{ij,low}^k) * x_{ij}^k \leq 0 \quad \forall i \in N, \forall j \in M_i^k \quad (2)$$

$$\sum_{j\in M_i^k} x_{ij}^k \leq 1 \quad \forall i \in N, \forall k \in K \quad (3)$$

$$\sum_{i\in N}\sum_{j\in M_i^k} z_{ij}^k \geq Q^k \quad \forall k \in K \quad (4)$$

$$x_{ij}^k \in \{0,1\} \quad \forall i \in N, \forall j \in M_i^k, \forall k \in K$$

$$z_{ij}^k \geq 0 \quad \forall i \in N, \forall j \in M_i^k, \forall k \in K$$

The coefficient C_{ij}^k is a constant and computed a priori as:

$$C_{ij}^k = \sum_{\hat{j}=1}^{j-1} P_{i\hat{j}}^k (Q_{i\hat{j},high}^k - Q_{i\hat{j},low}^k) \quad (5)$$

In this formulation provided by [44], it is assumed that K types of items are being bought which is a more generalized problem. Even when we set $K = 1$, the MIP formulation turns out to be an *NP-hard* problem to solve. Additional side constraints such as a limit on the number of winning suppliers, lot level constraints at the level of the lot as well as the supplier along with reservation prices increase the complexity of the decision problem.

The procurement mechanism is set up as multi-round sealed bid auction which is analogous to an English Auction. Here, once the bids are submitted, a central system solves the winner determination problem. The winning bids are communicated to the sellers who can then resubmit new bids. In the next section we examine the computational issues that arise in this procurement context.

2) Computational Issues: The model is developed to address the winner determination problem with the implicit assumption that agents participating in the auction have a bidding strategy in place, perhaps with the use of game theoretic analysis. This being the context, we restrict our attention to computational issues that arise at the mechanism level and neglect analysis of any computational issues at the agent (bidder) level. The MIP formulation in the previous section is a variation of the multiple choice knapsack problem which is NP-Hard. Although Knapsack Problems, from a theoretical point of view, are almost intractable as they belong to the family of NP-hard problems, several of the problems may be solved to optimality in fractions of a second [48] and can be considered as the simplest among NP-Hard problems in combinatorial optimization. This is because the knapsack problem exhibits special structural properties which makes it easy to solve. Dynamic programming techniques, branch-and-bound algorithms and polynomial time approximation schemes have been proposed to solve knapsack problems. For a detailed exposition of several of these methods refer to [48]. Kameshwaran [49] shows that multi-unit procurement with volume discount bids leads to piecewise linear knapsack problems and proposes a variety of exact and heuristic techniques to solve this class of problems.

C. Single Item, Multi-Unit Procurement with Strategic Sourcing Issues in Supply Chains

In the previous subsections, we examined auction mechanisms in automating simple and stylized supplier selection situations which coincide with a fairly operational view of procurement. When the supplier selection process within a supply chain setting is viewed, at a higher level of granularity, through a strategic lens, a larger set of issues emerges. A procurement manager is concerned with questions like: What is the impact of a sourcing decision on the total cost of procurement ? How does one structure the sourcing pool so that the total cost of procurement is minimized ? A partial list of important cost components that contribute to the total cost of procurement could include: price per unit, logistics cost, inventory holding costs, and lead time costs. Classical auction literature, however, has focused on price and ignored the impact of other costs on the sourcing decision.

A first step in incorporating these other cost components while making a strategic sourcing decision is taken by Chen, Janakiraman, Roundy, and Zhang [22], who provide a design of single item, multi-unit auction mechanisms that achieve overall supply chain efficiency while taking into account production and transportation costs. The concern is to bring together the business requirements within a global supply chain, economic / game theoretic desiderata, and computational issues in building the decision model.

The business problem addressed is as follows: A buyer has requirements, called consumption quantities, for a certain component at a set of geographically diverse locations. It is assumed that the buyer has private valuations of consumption quantities at the demand locations, which forms the consumption vector and that she will act strategically to maximize her utility. Multiple suppliers, each owning a set of production facilities, are available to satisfy this demand. Every supplier has a production cost, which can be described as a convex function of the quantities that he produces at his production locations. It is also assumed that each supplier is a rational, self interested player who is trying to maximize his payoff (payment received minus the production cost). In addition the buyer knows the per unit transportation cost along each link in the supply network and she pays for all shipments along the links.

A key economic requirement in any resource allocation problem, is to ensure that the allocation minimizes total system costs. An auction mechanism is no different. Efficient allocation and incentive compatibility are two of the key desiderata. The authors use VCG (Vickrey-Clarke-Groves) mechanisms in their formulation. VCG mechanisms are one family of

TABLE II

NOTATION FOR AUCTION T, AUCTION R AND AUCTION S

N	total number of supplier production facilities
K	number of suppliers
M	total number of buyer locations
N^k	set of production facilities owned by supplier k
k^n	index for supplier that owns production facility n
q_m	consumption at demand center m, $q_m > 0$
x_n	production quantity at production facility n
y_{nm}	quantity shipped from the production facility n to demand center m
z_{km}	$\sum_{n \in N^k} y_{nm}$, total quantity shipped to demand center m by supplier k
$C_k(\mathbf{x}_k)$	production cost function for supplier k ($\mathcal{R}^{\lvert N^k \rvert} \rightarrow \mathcal{R}$)
$F_k(\mathbf{x}_k)$	bidding function from supplier k ($\mathcal{R}^{\lvert N^k \rvert} \rightarrow \mathcal{R}$)

mechanisms which are known to be incentive compatible and efficient [37], [18].

1) Model Formulation: Chen, Janakiraman, Roundy, and Zhang [22] present three separate auction mechanisms - Auction T, Auction R, and Auction S. The first two mechanisms incorporate transportation costs explicitly whereas in the third model, only production costs are considered for the allocation decision and transportation decisions are made subsequently. This provides a means to compare the two approaches and the implications for total cost of procurement strategies. Before we present the models, the notation used is introduced in Table 2.

There are three dominant mechanisms for multi unit auctions: Pay-as-you-bid, uniform-price, and VCG auctions. From auction literature, it is known that VCG mechanisms are both incentive compatible and efficient. However they have not been widely used in practice where human agents are involved, the reasons being two-fold: first, the perception that auctioneers may take advantage of the truth telling by bidders has inhibited the wide acceptance of this mechanism; secondly, VCG mechanisms require a large number of intractable problems to be solved.

2) Auction T: In this auction mechanism, the buyer submits a fixed consumption vector $\mathbf{q}$ to the auctioneer. Supplier k submits to the auctioneer a bid function $F_k(\mathbf{x}_k)$ for supplying $\mathbf{x}_k$ units, for which he incurs a production cost $C_k(\mathbf{x}_k)$, $\mathbf{x}_k \in \mathcal{R}^{\lvert N^k \rvert}$. The supplier may or may not see the consumption vector.

The auctioneer decides the quantities awarded to each supplier, and the amounts transported from suppliers' production centers to buyer's demand locations by solving the following winner determination problem.

$$\min \sum_{k=1}^{K} \mathcal{F}_k(\mathbf{x}_k) + \sum_{n=1}^{N} \sum_{m=1}^{M} \tau_{nm} * y_{nm} \tag{6}$$

subject to:

$$\sum_{n=1}^{N} y_{nm} = q_m, m = 1, \ldots, M; \tag{7}$$

$$\sum_{m=1}^{M} y_{nm} = x_n, n = 1, \ldots, N; \tag{8}$$

$$y_{nm} \geq 0, m = 1, \ldots, M; n = 1, \ldots, N. \tag{9}$$

A Vickrey based payment rule, belonging to the more general truth-inducing VCG family described in [50], is used. The rule, in words, essentially is:

Payment to vendor k	=	Bonus payment on account of the value that the vendor k adds to the system by participating in the auction.	+	Bid of vendor k

That is, if $\pi(\mathbf{q})$ is the optimal value of the objective function for a given $\mathbf{q}$; $\mathcal{Q} = \{\mathbf{q} : \mathbf{q} > \mathbf{0}, \pi(\mathbf{q}) < \infty\}$ and we restrict $\mathbf{q} \in \mathcal{Q}$ to ensure sufficient supply capacity. If $(\mathbf{x^T}, \mathbf{y^T})$ is an optimal solution, and $\pi^{-k}(\mathbf{q})$ is the optimal value of the objective function with the additional constraint that the supplier k does not participate in the auction ($\mathbf{x}_k = 0$), the buyer will pay supplier k:

$$\psi_k^T(\mathbf{q}) = \pi^{-k}(\mathbf{q}) - \pi(\mathbf{q}) + F_k(\mathbf{x}_k^T) \tag{10}$$

While it is true that the payment rule induces rational suppliers to bid their true costs, $F_k(\mathbf{x}_k) = C_k(\mathbf{x}_k)$, irrespective of other suppliers' bids, it also results in adverse effects for the buyer. In situations where the production capacity is tight, and the production costs are sharply convex, the contribution that a supplier makes to the system can be significantly high resulting in disproportionately high payments even when production is at a low cost. Alternately, as pointed out by the authors, when suppliers' capacities are asymmetric, removing a supplier to solve the optimization problem may result in computing an infinite value for the contribution that is made, which is an undesirable consequence. To rectify these problems, the authors propose *Auction R.*

3) Auction R: In this auction mechanism, the winner determination (optimization) problem solved by the auctioneer retains the essential structure of *Auction T* except that the payment rule is modified. This modification results in much lower payments, compared to *Auction T*, by the buyer while simultaneously ensuring that the sellers bid their true costs. In essence, incentive compatibility is retained.

The key idea introduced to achieve this result is as follows: Here, the buyer submits a utility function $W(\mathbf{q})$, which is a proxy for the true consumption utility $U(\mathbf{q})$, in place of a consumption vector as in *Auction T.* The auctioneer solves a modified version of the winner determination (optimization) problem using a new payment rule. This rule follows the VCG payment structure but also incorporates the utility function $W(\mathbf{q})$ in computing the payments. The utility function essentially serves the role of a reservation price function for each unit of the item that the buyer might acquire. While in most auctions the payments made to a supplier is based on *bids from all suppliers*, in *Auction R*, part of the payment is determined by the proxy utility function acting as a reservation price function. This prevents unusually large payments.

There is however a *price to pay* for this improvement. In order to submit an optimal utility function $W^*(\mathbf{q})$, the buyer needs to know the suppliers' production cost functions. However this may not hold in reality. So the buyer will have to expend effort to at least get a probabilistic belief of the cost functions. This causes uncertainty in both payments and consumption quantities. Numerical examples to illustrate this effect are provided in [22].

4) Auction S: In order to compare the cost savings, if any, that could be achieved by taking an integrated view of sourcing decisions, the authors formulate *Auction S*. Here the buyer's sourcing decision is based only upon the bids submitted by the sellers, and the transportation costs are determined subsequently.

The buyer submits a consumption vector $\mathbf{q}$ as in *Auction T*. The auctioneer solves two optimization problems, one to determine allocation and payments and the other to optimize transportation costs, separately.

Winner Determination Problem:

$$\min \sum_{k=1}^{K} \mathcal{F}_k(\mathbf{x}_k) \tag{11}$$

subject to:

$$\sum_{n=1}^{N} y_{nm} = q_m, m = 1, \ldots, M; \tag{12}$$

$$\sum_{m=1}^{M} y_{nm} = x_n, n = 1, \ldots, N; \tag{13}$$

$$y_{nm} \geq 0, m = 1, \ldots, M; n = 1, \ldots, N. \tag{14}$$

If $\pi_S(\mathbf{q})$ is the optimal objective value, $\mathbf{x}^S$ the production vector, and $\pi_S^{-k}(\mathbf{q})$ the optimal objective value without supplier k, the buyer's payment to supplier k is given by the rule:

$$\psi_k^S(\mathbf{q}) = \pi_S^{-k}(\mathbf{q}) - \pi_S(\mathbf{q}) + \mathcal{F}_k(\mathbf{x}_k^S) \tag{15}$$

We can observe that this payment rule still retains the VCG structure, and hence the suppliers will submit their true cost functions. Subsequently the transportation costs are determined by solving the following optimization problem:

Transportation Problem:

$$\min \sum_{n=1}^{N} \sum_{m=1}^{M} \tau_{nm} * y_{nm} \tag{16}$$

subject to:

$$\sum_{n=1}^{N} y_{nm} = q_m, m = 1, \ldots, M; \tag{17}$$

$$\sum_{m=1}^{M} y_{nm} = x_n^S, n = 1, \ldots, N; \tag{18}$$

The buyers total outflow, $\kappa_S(\mathbf{q})$, is given by $\kappa_S(\mathbf{q}) = \sum_{k=1}^{K} \psi_k^S(\mathbf{q}) + \sum_{n=1}^{N} \sum_{m=1}^{M} \tau_{nm} * y_{nm}^S$. The numerical experiments clearly show that *Auction S* minimizes total production costs but leads to higher supply chain costs than Auctions T and R.

5) Computational issues: The crucial contribution of this model has been to take an integrated view of the sourcing problem by combining the pricing and the transportation decisions. The mechanism incorporates game theoretic considerations in supply chain formations when products are sourced globally for demand points that are distributed geographically. Since the mechanism is incentive compatible for the suppliers, the complexity of evolving an optimal bid strategy is simply reduced to reporting the actual production costs, thereby eliminating the need for complex modeling of competitors' behavior. At the mechanism level however, $(K+1)$ optimization problems need to be solved to decide the allocations and payments. Further, since the mechanism is not incentive compatible for the buyer, the buying agent needs to solve an optimization problem to decide an optimal bidding strategy.

D. Summary and Current Art

In this section we reviewed models proposed to handle the procurement of multiple units of a single item, with a single attribute - price as the criterion for decision making. In the first model, we illustrated the game theoretic considerations that influence the bidding behavior of agents. In the second model, in the absence of game theoretic requirements, we pointed out the computational complexity of the winner determination problem in a more complex sourcing situation. The third model brought together the game theoretic as well as computational issues that complicate the sourcing problem. This was done to illustrate the fact that in the absence of proper mechanism design, the buyer could end up leaving money on the table.

In Section VII, we present the case study of MARS incorporated [6] which shows the successful application of single item, multi-unit procurement auction with volume discount bids from suppliers in a real-world setting. The computational challenges involved in the winner determination problem there are described in [46], [44]. Kameshwaran [49], in his recent work, has shown that single item, single attribute, multi-unit procurement with volume discount bids leads to piecewise linear knapsack problems to be solved. In his work, Kameshwaran has developed several algorithms (exact, heuristic-based, and fully polynomial time approximation schemes) for solving such knapsack problems.

Kothari, Parkes, and Suri [51] consider single-item, single attribute, multi-unit procurement auctions where the bidders use marginal-decreasing, piecewise constant functions to bid for homogeneous goods. The objective is to minimize cost for the buyer. It is shown that the winner determination problem is a generalization of the classical 0/1 knapsack problem, and hence NP-hard. Computing VCG payments also is addressed. The authors provide a fully polynomial time approximation scheme (FPTAS) for the generalized knapsack problem. This leads to an FPTAS algorithm for allocation in the auction which is approximately strategy proof and approximately efficient [51]. It is also shown that VCG payments for the auctions can be computed in worst-case $O(T \log n)$ time, where T is the running time to compute a solution to the allocation problem.

Dang and Jennings [52] consider multi-unit auctions where the bids are piece-wise linear curves. Algorithms are provided for solving the winner determination problem. In the case of multi-unit, single-item auctions, the complexity of the clearing algorithm is $O(n(K+1)^n)$ where n is the number of bidders and K is an upper bound on the number of segments of the piecewise linear pricing functions. The clearing algorithm therefore has exponential complexity in the number of bids.

To summarize, the two main issues in single item, multi-unit, single attribute auctions are (1) to reduce the complexity of the winner determination problem and (2) to make the mechanism strategy proof. There is still scope for improving the efficiency of the algorithms. In the next section, we review models that address procurement scenarios with one more degree of complexity - sourcing decisions based upon multiple attributes.

V. Single Item, Multi-Attribute Procurement Mechanisms

The procurement mechanisms of the previous section involve a single attribute based on price. In practice, these mechanisms address only a limited band of the negotiation spectrum, whereas sourcing decisions involve multiple criteria - both quantitative and qualitative [53]. Benyoucef, Ding, and Xie [45] present an exhaustive, hierarchical list of criteria that are used in evaluating and selecting suppliers. Incorporating these criteria into an automated negotiation tool to support sourcing decisions has been the holy grail of purchasing professionals, industrial engineers, and computer scientists. Many software solution vendors now support multi attribute reverse auctions in their e-sourcing solutions. Weighted, multi-parameter, multi-line item request-for-quotes (RFQ's) and reverse auction capabilities are provided by Ariba, freemarkets, and Procuri; i2 Technologies goes one step further and claims to support all these within an optimization module that allows business level constraints to be incorporated [54]. Since these are commercial products, it is not possible to independently verify the mechanics of the automated sourcing solutions. However, we conjecture that they use one or more of the known approaches to multiple criteria decision analysis (MCDA) such as additive value models, analytic hierarchy process (AHP), lexicographic ordering, multi-attribute utility theory (MAUT), simple multi-attribute rating technique (SMART), and traditional weight assessment. For a detailed treatment of these approaches, we refer the reader to [55].

In this section, our discussion focuses on single item, multi-attribute procurement problems to investigate (1) the problem scenarios addressed, (2) solution approaches, and (3) computational and game theoretic issues.

A. *Issues in Multi-Attribute Procurement*

Simply defined, multi-attribute procurement refers to the decision process related to the determination of a contract by considering a variety of attributes involving not just price but also aspects such as quality, delivery time, contract terms, warranties, after sales service, etc. In practice, multi-attribute procurement scenarios come in various hues and shades. To aid in analysis, we group these problems into three distinct categories which we believe adequately reflect the issues to be considered from a computational / automation point of view. The groups and their characteristics are:

- Multiple attributes are known a priori and are uncorrelated; individual attributes have point values. The suppliers provide *point bids* where each bid has a single price and each attribute has a single value, either provided by the supplier or computed by the buyer.
- Multiple attributes are known a priori and are uncorrelated; each attribute can take an individual value from a domain of possible values for the attribute. The suppliers provide *configurable bids* which specify multiple values and price markups for each attribute.
- The multiple attributes are not known a priori and they are uncorrelated. The suppliers may provide *point bids* or *configurable bids*. This is not unlike many negotiation situations where the buyer has only a rough idea of her requirements but relies on suppliers to educate him about attributes relevant to the procurement decision.

A further level of complexity is involved when the attributes are correlated in each of the above cases. Also, each of the above scenarios can occur in combinations.

In the first scenario above, if we assume that there exists some decision rule which, as a function of all the multiple attributes, ranks the bids, then the winner determination problem is relatively straightforward. In the latter two cases, however, the options are combinatorial in nature and hence the winner determination problem will have exponential complexity. This raises the issue of compactness of information or bid representation, which we come back to later. For now, we focus on methods to *develop* the decision rule for ranking of bids.

Traditional approaches to developing the decision rule have relied on either a hierarchical elimination process or on weighted average techniques. Since determining the hierarchy or the choice of weights is not always straightforward, especially in the face of a large number of attributes, many sophisticated approaches, including the use of optimization tools, have been proposed which we review next.

1) Elimination Methods: In this method, at each level, we eliminate from the bid list, bids that do not satisfy the selection rule. The selection rule may be a *conjunctive rule* or a *lexicographic rule*. In either case, a hierarchy of the attributes needs to be established in the order of their importance, which is fuzzy for most decision makers. To overcome this handicap, optimization based approaches have been devised. We briefly describe these techniques below:

Lexicographic Ordering: Here, on the first level, we select the most significant criterion and we compare bids based on this. If a bid satisfies this criterion much better than the other suppliers, then it is chosen, otherwise the bids are compared with respect to the second criterion, and so on.

Satisficing: In this technique we set minimum levels for every attribute except one, which is the target attribute, such as price. We select bids which satisfy the minimum levels and choose the one with the optimal value of the target. It is also possible to iterate through the minimum levels.

Analytic Hierarchy Process (AHP): This is an analytical tool, supported by simple techniques, that enables people to explicitly rank tangible and intangible factors against one another for the purpose of resolving conflict or for setting priorities. The process involves structuring a problem from a primary objective (e.g. selecting the best bid) to secondary levels of objectives (e.g. performance objectives, quality needs, etc.). Once these hierarchies have been established, a pairwise comparison matrix of each element within each level is constructed.

Goal Programming: This is a way to handle multiple objectives in what would otherwise be a LP. The basic concept is to set "aspiration levels" (targets) for each objective and prioritize them. One would then optimize the highest priority objective with respect to the original ("hard") constraints. Next, a constraint is added saying that the first objective function's value must be at least as good as what was achieved or the aspiration level, whichever is worse. Now the second objective is optimized, turned into a constraint, etc.

2) Weighted Average Methods: The weighted average methods essentially rely on the introduction of a *virtual currency* which expresses the overall utility of a bid to the buyer. The computation of the virtual currency is based upon the utility function specified by the buyer and bids that achieve the best overall utility are declared winners. It is obviously of interest to the buyer to specify the *best possible* utility function. We briefly describe some of these techniques below:

Traditional weighted average technique: Purchasing professionals have traditionally relied upon assigning *weights* to individual attributes and using a simple additive rule to derive the virtual currency. This is not dissimilar to approaches in micro-economic theory for developing utility functions. This has been further refined by the swing weighting approach described in [25]. The application of this approach can be severely restricting when the number of attributes to be considered is large.

Weight Determination Based on Ordinal Ranking of Alternatives (WORA): This approach recognizes the pitfalls in using the weighted average technique and hence relies on linear programming techniques to compute the optimal weights for each of the attributes. We detail this approach in the next section.

Inverse Optimization Methods: This technique is an improvement over WORA, in the sense that it does not rely on a single central agency (the buyer) to provide inputs to compute the optimal decision rule. Rather it uses a novel and intelligent technique based on inverse optimization to gather information distributed among various agents (sellers) in the marketplace to develop the optimal scoring (decision) rule.

In the following sections, we emphasize two different approaches that have been proposed to develop multi attribute procurement mechanisms.

B. Additive Value Model Based on Ordinal Ranking of Alternatives

A straightforward approach to multi-attribute procurement is to assume that the utilities of each of the attributes are additive in nature and hence a virtual currency, like the stock market index can be developed. Formally, we have a vector Q of relevant attributes of a bid. We index the attributes by i and the set of bids B by j. A vector $\mathbf{x}_j = (x_j^1, \ldots, x_j^n)$ is specified, where x_j^i is the level of the attribute i in bid b_j. In the simple case of an additive utility function $U(\mathbf{x}_j)$, each attribute is evaluated through a utility function $U_i(\mathbf{x}_j^i)$ and the overall utility is the sum of all weighted utilities. This produces a virtual currency to be used in mechanisms of the type proposed for single attributes. The crucial issue however is the following: *How are the weights or the utility function decided*? Naive approaches include the elicitation of buyers preferences through the design of smart web forms [1]. More recently techniques based on decision analysis have been proposed by [25] and [23] which we describe next.

The WORA technique has been developed as part of an application framework to provide buyer side decision support for e-sourcing [25]. It is based on the realization that the buyer can make deductions about the superiority of bids through simple pairwise comparisons. By making many such comparisons, not entirely exhaustive, it is possible to build a larger information set to elicit *intelligently* the scoring function. This is done in a two step process.

In the first step, sample ordinal rankings of bids are provided by the buyer. They are of the form $B_1 \succ B_2 \succ B_3$. These rankings are checked for *intransitive preferences* and *dominance violations*. These sample rankings are then transformed into constraints to a linear program, which then generates estimates for the decision maker's weights. The LP is formulated as follows:

Let $B = \{B_1, B_2, \ldots, B_k\}$ be a subset of bids that are ranked in the order $B_1 \succ B_2 \succ B_3 \succ \ldots \succ B_k$. The score S_i of each bid B_i is computed as:

$$S_i = \sum_{j \in J} w_j * F(a_{ij}) \quad \forall i \tag{19}$$

where the weights w_j are unknown and j is the number of the attribute, and these satisfy the bid rankings. The LP is:

$$\begin{gathered} \text{Maximize } 0 \\ \text{subject to:} \\ S_1 \geq S_2 \\ S_2 \geq S_3 \\ \vdots \\ S_{k-1} \geq S_k \\ \textstyle\sum_{j \in J} w_j = 1 \\ w_j \geq 0 \text{ for each j} \end{gathered}$$

A feasible solution to this LP can be found and results in an estimate for the weights to be used in the scoring rule. The authors also provide some numerical experiments to show the efficacy of the technique. These weights are then used within a standard single attribute like procurement mechanism with the *virtual currency*, obtained by combining price and all other attributes, substituting for *price*.

While this technique is an improvement over ad-hoc weight assignment models, it still relies on a single buying agent to indicate an ordinal ranking in order to come up with an optimal scoring function. This approach does nothing to exploit the cost complementarities that production systems of the suppliers may exhibit in providing certain attribute levels. In such cases it may be beneficial for the buyer to understand the nature of the suppliers cost functions in terms of the non-price attributes. Understandably, it is not likely to be in the interest of suppliers to part with this information. In the next section we discuss one approach which tries to overcome this problem.

C. Additive Value Model with Inverse Optimization Techniques

In some procurement scenarios where the establishment of a contract depends upon multiple attributes (price, quality, delivery time, features and options, etc), a Request-for-Quote (RFQ) process is preferred. In this process, the buyer announces a scoring rule in terms of the bid price and the various attributes to be considered. It is not uncommon for the buyer to change the scoring rule to reflect any new information that has been gleaned during the RFQ/negotiation process. This idea is formalized in the eRFQ mechanism in [23] which is designed to address a procurement scenario with the following characteristics and assumptions:

- A single item with multiple attributes is to be procured. The attributes are indexed by $a = 1, \ldots, A$; s indexes the S suppliers; p indexes the P cost (and utility) parameters and $r = 1, \ldots, P+1$ indexes the rounds of the auction.
- Each bid submitted by a supplier is of the form $(p, x_1, \ldots, x_A)$ where p denotes the price and x_a is the magnitude of non-price attributes which are continuous, nonnegative variables.
- Supplier s's cost function $\sum_{a=1}^{A} c_{as}(x_a, \theta_{as1}, \ldots, \theta_{asP})$, is additive across attributes and c_{as} is increasing, convex and twice continuously differentiable in x_a.
- The auctioneer is assumed to know the form of the suppliers cost function but not the actual parameter values $(\theta_{as1}, \ldots, \theta_{asP})$
- $\sum_{a=1}^{A} v_a(x_a, \psi_{a1}, \ldots, \psi_{aP}) - p$, is the true utility function of the buyer and the scoring rule is $\sum_{a=1}^{A} v_a(x_a, \phi_{a1r}, \ldots, \phi_{aPr}) - p$, in round $r = 1, \ldots, P$, which is increasing and concave in x_a. Further, to guarantee existence of solutions to the optimization problem, described later, a set of technical requirements are imposed upon the cost, scoring and valuation functions.

The eRFQ mechanism is based upon an open ascending auction format consisting of $P+1$ rounds. The first P rounds enable learning of the P parameters, through *Inverse Optimization*, and the last round is with an optimized scoring rule. Ahuja and Orlin [56] describe Inverse Optimization in the following manner:a typical optimization problem is a forward problem because it identifies the values of observable parameters (optimal decision variables), given the values of the model parameters (cost co-efficients, right-hand side vector, and the constraint matrix). An inverse optimization problem consists of inferring the values of the model parameters (cost co-efficients, right-hand side vector, and the constraint matrix), given the values of observable parameters (optimal decision variables).

In each round of the auction, the buyer announces a scoring rule in response to which suppliers submit bids. Activity rules and transition rules are imposed to move from one round to the other. In each round the buyer ranks the bids according to the latest scoring rule and announces the rankings without revealing the bidders or the actual bids. The winner determination, at the end of $P+1$ rounds, is based simply upon an English auction like rule, with the bidder providing the highest utility at the end of $P+1$ rounds being offered the contract at his bid price.

The key questions that arise are: (1) what is the likely bidding behavior of the suppliers; (2) how does the buyer estimate the suppliers' cost functions; and (3) how is the optimal scoring rule determined after *learning* the cost functions.

Bidding Behavior of Suppliers: The supplier is assumed to follow a *myopic best response* bidding behavior which is in line with the approaches used in [57], and [58]. Here, the supplier chooses his bid such that he maximizes his current profit with the assumption that other suppliers do not change their bids. The bid is chosen by solving the following Non-Linear Optimization problem:

$$\max_{p, x_1, \ldots, x_A} p - \sum_{a=1}^{A} c_{as}(x_a, \theta_{as1}, \ldots, \theta_{asP}) \tag{20}$$

subject to

$$\sum_{a=1}^{A} v_a(x_a, \phi_{a1r}, \ldots, \phi_{aPr}) - p = S + \epsilon \tag{21}$$

In the final round however, the constraint would be:

$$\sum_{a=1}^{A} f_a(x_a) - p = S + \epsilon \tag{22}$$

While the bidding behavior does not include a game theoretic analysis of competing suppliers, it still requires bidders to be sophisticated enough to solve optimization problems. This is striking a middle ground with respect to the bidders' rationality.

Estimating cost functions of the suppliers: By virtue of the auction design, the auctioneer at the end of P rounds has for each attribute a and each supplier s, P equations. These P equations obtained by solving the first order conditions for $a = 1, \ldots, A$,

$$\frac{\delta v_a(x_a, \phi_{a1r}, \ldots, \phi_{aPr}}{\delta x_a} = \frac{\delta c_{as}(x_a, \theta_{as1}, \ldots, \theta_{asP})}{\delta x_a} \tag{23}$$

form a set of simultaneous linear equations. By solving this set of equations for each supplier s the true cost parameters for each attribute a can be obtained.

Computing the optimal scoring rule: After learning the suppliers cost functions, the optimal scoring rule for round $P+1$ is computed by solving the following optimization problem:

$$\max_{f_a}\left\{\sum_{a=1}^{A} v_a(x^*_{a1},\psi_{a1},\ldots,\psi_{aP})-\sum_{a=1}^{A} f_a(x^*_{a1})\right\}$$
$$+\left\{\sum_{a=1}^{A} f_a(x^*_{a2})-\sum_{a=1}^{A} c_{a2}(x^*_{a2},\theta_{a21},\ldots,\theta_{a2P})\right\} \quad (24)$$

subject to:

$$S_s=\sum_{a=1}^{A} f_a(x^*_a)-\sum_{a=1}^{A} c_{as}(x^*_a,\theta_{as1},\ldots,\theta_{asP}) \quad (25)$$

$$S_2>\epsilon \quad (26)$$

$$S_1>S_2+\epsilon \quad (27)$$

The objective function maximizes the buyer's utility with the last three terms of (24) making up the winning suppliers price; (25) is supplier s's maximum drop-out score; (26) and (27) ensure that the top two suppliers participate in round $P+1$.

In the model described above, assumptions about (1) undistorted bidding behavior by suppliers and (2) knowledge of the form of the suppliers' cost functions may be untenable in practice. The authors propose several extensions to the basic model in order to make it more robust.

First, in developing the scoring rule for the last round, the authors envisage three problems: (a) a difficult mathematical programming problem needs to be solved, (b) the scoring rule may turn out to be too complex, and (c) the scoring rule may force the losing supplier to submit bids with negligible values of non-price attributes. To overcome these problems the authors propose to (1) changing the method of finding the best competitor, (2) providing the scoring rules in graphical form, and (3) introducing lower bound constraints on the attribute levels in the final round.

Secondly, the bidding behavior of suppliers may not follow the *undistortedness* assumption either because of strategic intentions of the supplier or the lack of sophistication on their part. This would result in an inconsistent set of simultaneous linear equations. The authors suggest using a weighted average least squares procedure to reduce the effects of bid distortion.

D. Summary and Current Art

In this section we reviewed mechanisms designed for the procurement of items with multiple attributes. We briefly reviewed the approaches to multi-criteria decision making and identified two broad categories of techniques - elimination methods and weighted average methods. The crucial issue in multi criteria procurement is the assignment of weights to each of the attributes to facilitate the development of a scoring function which captures the buyers' utility. Two *intelligent* approaches - the first relying on a central agency to indicate a pairwise preference among a sample of received bids and the second based upon estimating the suppliers cost functions, were detailed.

Currently, developing efficient approaches for multi-attribute procurement is an active research area. The reader is referred to [59], [60], [61], [62], [49] for some recent work. The papers [59], [60], [61] build upon the approaches described above. Kameshwaran and Narahari [62] have proposed an approach based on goal programming. Goal programming (GP) is one of the tools of choice for multi criteria decision analysis [63]. In [62], the authors show that **GP** can be used to model procurement scenarios where suppliers provide bids with *configurable offers*. Here the bids are assumed to be piece-wise linear and the buyer has a hierarchy of goals or aspiration levels which are to be satisfied. The authors propose the use of Weighted GP, Lexicographic GP, and Interactive Sequential GP techniques to solve the multi-attribute procurement problem.

There are many issues that remain unresolved in multi-attribute procurement. No single approach seems to work uniformly well and it is an intrinsically challenging problem. Much work remains to be done in all the areas: winner determination algorithms, payment rules, achieving truth revelation, etc.

In the next section, we review mechanisms that enable the procurement of multiple items with a single attribute (namely price) as the criterion for decision making.

VI. Multi-Item, Single Attribute Procurement Mechanisms

In the previous sections, we reviewed mechanisms that support single item procurement. In one of the mechanisms, we discussed the inclusion of logistics costs as an additional element influencing the procurement decision. Clearly such supply chain criteria are of crucial importance to procurement managers responsible for large global supply chains. Typically purchase requests within such large purchasing organizations provide opportunities to exploit complementarities in logistics costs and often in production costs too. For instance, in one of the negotiation scenarios depicted in Section II.A, a family of cutting tools may be procured by a series of sequential reverse auctions, one for each of the items. This has at least two consequences: Firstly, the price that a supplier may be willing to offer may depend in complicated ways on what other items he wins, and since there is uncertainty associated with this, the suppliers have no incentive to bid aggressively. Secondly, the suppliers do not have an opportunity to express their unique complementarities in production costs and hence the buyer cannot exploit the economies of scope associated with bundling the demands. In such cases it may be beneficial to allow the suppliers to bid on combinations of items rather than on single items. Such auctions are called *combinatorial auctions*.

Simply defined, a combinatorial auction (CA) is a mechanism where bidders can submit bids on combinations of items. The winner determination problem is to select a winning set of bids such that each item to be bought is included in at least one of the selected bids, and the total cost of procurement is minimized. In this section we first present the crucial issues that arise when CA's are applied to procurement settings. We

then review approaches to modeling multi-item procurement in supply chain settings which take business and capacity level constraints into consideration.

A. Issues in Multi-Item Procurement

Important issues in combinatorial auctions are well surveyed in [14], [15], [16]. In the multi-item procurement case, when suppliers are allowed to respond with combinatorial bids, the winner determination problem becomes a weighted set covering problem, which is known to be NP-hard. In addition, since the bidders can submit bids on combinations of items, the representation of the bid is also a crucial implementation issue. Bidding language issues are discussed in [64], [65].

As opposed to single item procurement scenarios, in multi-item procurement scenarios, the range of issues to be considered are vastly expanded because practical business level issues and constraints need to be included in the decision model. These could include exclusion constraints (for example, item A cannot be procured from supplier X), aggregation constraints (for example, at least two and at most five suppliers need to be selected for goods of category B), and exposure constraints (for example, not more than 25% of the procurement value should be assigned to any one supplier) [62], [6]. By including these constraints in the decision model, a sensitivity analysis of side constraints may also prove to be a useful tactical input to procurement planners.

In strategic sourcing scenarios where voice-based supplier relationships dominate [66], the auction based models, though criticized for their emphasis on price as the only basis for contract determination, may yet prove useful. Where production costs are sharply convex, due to either overtime costs or capacity shortfalls, the procurement costs of buyers or profitability of suppliers may be severely affected. In these cases, auction based procurement mechanisms can provide a useful handle on prudent capacity management. We investigate each of the above issues in subsequent sections.

B. A Single Round Combinatorial Procurement Mechanism

As indicated above, the reverse combinatorial auction problem is a set covering problem, which is NP-hard. Additional side constraints make a fundamental impact on the problem. Even finding a feasible solution when exposure constraints are in place is NP-hard. The basic formulation of the problem and the additional side constraints are presented below and solution techniques are discussed thereafter. The following formulation is from [44], [6]. Table 3 provides the notation.

1) Mathematical Formulation: K is a set of items, where for each $k \in K$ there is a demand d^k. Each supplier $i \in N$ is allowed up to M bids indexed by j. Associated with each bid B_{ij} is a zero-one vector a^k_{ij}, $k = 1, \ldots, |K|$ where $a^k_{ij} = 1$ if B_{ij} will supply the entire lot corresponding to item k, and zero otherwise. Associated with each bid B_{ij} is price p_{ij} at which the bidder is willing to supply the combination of items in the bid. A mixed integer programming (MIP) formulation can be written as follows:

TABLE III

NOTATION FOR COMBINATORIAL PROCUREMENT

K	set of items to be procured
$k \in K$	index for an item
d^k	number of units of item k demanded
N	set of suppliers
$i \in N$	index for a supplier
M	set of bids allowed for a supplier
$j \in M$	index for a bid
B_{ij}	bid j of supplier i
a^k_{ij}	0-1 variable which takes value 1 iff B_{ij} will supply the entire lot corresponding to item k
p_{ij}	price associated with bid B_{ij}
$W_{i,min}$	minimum quantity that can be allocated to supplier i
$W_{i,max}$	maximum quantity that can be allocated to supplier i
x_{ij}	decision variable that takes value 1 iff B_{ij} is allocated
y_i	indicator variable that takes value 1 iff supplier i is allocated any lot
S_{min}	minimum number of winners required
S_{max}	maximum number of winners allowed

$$\min \sum_{i \in N} \sum_{j \in M} p_{ij} x_{ij} \tag{28}$$

$$S.T. \quad \sum_{i \in N} \sum_{j \in M} a^k_{ij} x_{ij} \geq 1 \quad \forall k \in K \tag{29}$$

$$x_{ij} \in \{0,1\} \qquad \forall i \in N, \quad \forall j \in M$$

$$W_{i,min} y_i \leq \sum_{k \in K} \sum_{j \in M} a^k_{ij} * d^k * x_{ij} \forall i \in N \tag{30}$$

$$\sum_{k \in K} \sum_{j \in M} a^k_{ij} * d^k * x_{ij} \leq W_{i,max} * y_i \qquad \forall i \in N \tag{31}$$

$$\sum_{j \in M} x_{ij} \geq y_i \qquad \forall i \in N \tag{32}$$

$$S_{min} \leq \sum_{i \in N} y_i \leq S_{max} \tag{33}$$

$$Y_i \in \{0,1\} \qquad \forall i \in N$$

$W_{i,min}$ and $W_{i,max}$ are the minimum and maximum quantities that can be allocated to any supplier i; Constraints (30) and (31) restrict the total allocation to any supplier to lie within $(W_{i,min}, W_{i,max})$. y_i is an indicator variable that takes the value 1 if supplier i is allocated any lot. S_{min} and S_{max} are respectively the minimum and maximum number of winners required for the allocation and constraint (33) restricts the winners to be within that range.

2) Solution Approach and Discussion: Although the decision model is NP-hard, integer programming techniques are known to be effective in solving problems with 500 items and up to 5000 bids [6]. For the purpose of this paper, the authors use IBM's OSL (Optimization Solutions and Library) to solve the IP formulation. From the experiments that were conducted, the following conclusions could be derived:

- Firstly, varying the aggregation constraint seems to have a large impact on the computation time. This is because, as we commented earlier, the problem of finding a feasible solution itself is NP-complete.
- Secondly, the min-max exposure constraints also have a significant effect on the computational time. In some sense, the exposure constraint could itself be a proxy for the aggregation constraint and hence the behavior appears similar.

C. An Iterative Reverse Dutch Auction for Combinatorial Procurement

In the previous section, we discussed a purely computational view of the multi-item procurement problem without regard to economic desiderata. It is however important for a variety of reasons to lend credence to economic issues too in the modeling and analysis of multi-item procurement. Firstly, we would like to ensure that procurement contracts are allocated to those that *value them most*. In the absence of economic analysis, the game is open for suppliers to indulge in strategic bidding behavior in an effort to extract the maximum possible surplus utility from the negotiation. This is especially true when single shot mechanisms are used. Secondly, even if multi-round combinatorial auctions are used where allocation and pricing information is disclosed at the end of each round, it is not clear to suppliers as to how they need to reformulate their bids. The two issues together may prompt wasteful usage of resources by each supplier in trying to *outsmart* the buyer and other suppliers. One way to amend the situation is to design an incentive compatible mechanism, that is. a mechanism which provides incentives for truthful bidding thereby making it the dominant strategy for all participants in the mechanism.

Generalized Vickrey Auctions (GVA) generalize the single item second price auction (Vickrey auction) proposed in [38]. This is an incentive compatible mechanism for combinatorial auctions, which can be applied to the procurement context [24]. However, a couple of issues need to considered. First, the GVA is not strongly budget balanced, and secondly it requires an optimal solution to the allocation problem which is NP-hard. In the absence of an optimal solution to the allocation problem, the resulting mechanism, whose allocation is obtained through some approximation scheme, is no longer incentive compatible [50]. However, iterative algorithms for combinatorial auction problems have been proposed by [67] and [68] which try to resolve the tension between economic and computational efficiencies. In a similar vein, Biswas and Narahari [24] have proposed an iterative reverse Dutch auction scheme for combinatorial procurement auctions which we discuss next.

1) Integer Programming Formulation for the Reverse Dutch Auction: The basic idea behind this approach is to formulate the procurement problem as a weighted set covering problem and use the Dutch auction format to develop an iterative solution scheme. This approach reduces the computational complexity by breaking up one large GVA into several smaller GVA's. The iterative algorithm itself is motivated by [69], and involves a two step process: (1) progressively increasing the *average reserve price* of the items in each round, and (2) allocating items for which bids satisfy the reserve price. Classical (forward) Dutch auctions are decreasing auctions which have been typically used for multi-unit homogeneous items. In the single unit Dutch auction the auctioneer begins at a high price and incrementally lowers it until some bidder signals acceptance. Similarly in the multi-unit case the price is incrementally reduced till all the items are sold or the seller's reserve price is reached.

In the reverse auction for procurement the buyer has a procurement budget and tries to procure a bundle of items at minimal cost not exceeding the procurement budget. She starts with a low initial willingness to pay (say equal to zero) and keeps on increasing the willingness to pay until the total bundle is procured or the budget limit is reached. This total budget cannot be divided linearly into budget for each item because of the complementarities involved.

The iterative mechanism proposed in [24], [70] consists of multiple bidding rounds denoted by $t \in dZ_+$ ($t = 0$ is the initial round). The buyer sets $W(B_t)$, maximum willingness to pay for the remaining bundle B_t to be procured in round t. The pricing of items is not linear, therefore the cost of the allocated bundles cannot be divided into price of individual items. Therefore we compute p_t, the average willingness of the buyer to pay for each item in round t.

$$p_t = \frac{W(B_t)}{|B_t|}, \text{where } B_t \neq \phi \tag{34}$$

The payment made by the buyer for the subset S_t in iteration t is $V^*(S_t)$. The average price paid by the buyer for each item procured is $v_t = \frac{V^*(S_t)}{|S_t|}$. Iterations in which no items are procured are ignored.

The reserve price of the seller for any bundle S in iteration t is $|S|v_{t-1}$. GVA with reserve prices [71] used in each iteration to solve the allocation and payment problems efficiently. The bundle procured in round t is denoted by S_t. Therefore the integer programming formulation of the GVA problem with reserve prices in iteration t becomes

$$\begin{aligned}
V^*(S_t) \quad & = \min \sum_{j \in N} \sum_{S \subseteq M} v_j(S) y(S,j) \\
s.t. \quad & \sum_{S \ni i} \sum_{j \in N} y(S,j) \geq 1 \;\; \forall i \in M \\
& \sum_{S \subseteq M} y(S,j) \leq 1 \;\; \forall j \in N \\
& v_j(S) y(S,j) \geq |S| v_{t-1} \;\; \forall S \subseteq M, \forall j \in N \\
& \sum_{j \in N} \sum_{S \subseteq M} v_j(S) y(S,j) \leq W(B_t) \;\; \forall S \subseteq M \\
& y(S,j) = 0,1 \;\; \forall S \subseteq M, \forall j \in N \qquad (35) \\
& \qquad (36)
\end{aligned}$$

The notation for the Iterative Reverse Dutch Auction (IRDA) algorithm is provided in Table 4.

TABLE IV

NOTATION FOR ITERATIVE REVERSE DUTCH AUCTION ALGORITHM

t	iteration number
B_t	bundle remaining to be procured in iteration t
(S_t)	set procured in iteration t
$V^*(S_t)$	buying price of the set S_t in iteration t
v_t	average buying price of each item in iteration t
p_t	average price set by the auctioneer in iteration t
$W(B_t)$	maximum price set by the auctioneer for the bundle B_t in iteration t
$v_j(S)$	valuation of set S to seller j
$y(S,j)$	indicator variable that takes value 1 iff bundle $S \in M$ is allocated to agent $j \in N$
ϵ	increment in buyer's willingness to pay

The IRDA Algorithm: As opposed to a naive approach, the IRDA algorithm relies on choosing an increment in each round such that it is based on the size of the bundle to be procured.

1) Suppose the buyer's initial willingness to pay for the entire bundle B_0 is zero i.e. $W(B_0) = 0$. Therefore the willingness to pay for each item is also zero i.e. $p_0 = 0$. Since no sellers are likely to be interested to bid at this price, therefore
$$V^*(S_0) \ = v_0 \ = \ 0$$
2) Increment the average willingness to pay for each item by ϵ to $p_1 = v_0 + \epsilon$. This actually means that the buyer's willingness to pay for the bundle B_1 is changed to $W(B_1) = |B_1| \times p_1$. We assume that the increment ϵ in every iteration is constant. The reserve price of any bundle S for the sellers becomes $|S|v_0$.
3) Solve the allocation problem if there are any bids i.e. for iteration $t = 1$ solve the Eq. 35 and calculate v_1. This is again a combinatorial optimization problem. But this is much smaller than the complete problem.
4) Allocate the subsets to the winners. Remove the allocated items from the set to be procured and increment the average willingness to pay for each item to $p_2 = v_1 + \epsilon$, i.e. the maximum willingness of the buyer to pay for the remaining bundle B_2 is $W(B_2) = |B_2| \times p_2$. The new reserve price of any bundle S of items for the sellers is $|S|v_1$.
5) Go to step 3 and repeat until the buyer can procure the entire bundle or the upper limit i.e. the total procurement budget is reached . In any iteration t the following condition should be satisfied:
$$\text{total procurement budget} \ \geq \ W(B_t) + \sum_{i=0}^{t-1} V^*(S_i)$$

This approach to the combinatorial procurement problem, solves the problem of capturing cost complementarities. However, in typical strategic procurement settings, capacity planning at suppliers is a crucial task meriting detailed attention if supply lines are not to be disrupted. This planning of capacity and allocation of contracts can be significantly difficult when multiple contracts are to be established simultaneously. We discuss this issue in the next section.

TABLE V

NOTATION FOR PROCUREMENT UNDER CAPACITY CONSTRAINTS

m	number of components
j	index for components, $j = 1, \ldots, m$
q_j	number of units of component j to be procured
n	number of suppliers
i	index for resources (suppliers), $i = 1, \ldots, n$
c_i	capacity of supplier i
a_{ij}	amount of resource i required for component j
t	index that represents auction rounds
$b_{ij}(t)$	bid submitted in round t by supplier i for any quantity between 0 and q_j
$x_{ij}(t)$	decision variable for bid $b_{ij}(t)$

D. An Iterative Procurement Mechanism for Capacity Constrained Environments

In some strategic sourcing settings, where suppliers are looked upon as extensions of the enterprise, it is imperative to engage in prudent capacity management. Failure to do so could result in production line disruptions and high overtime costs. So when making multi-item procurement decisions, even when the product attributes do not show complementarities in costs, but share resources it is necessary to factor in capacity planning at least at the aggregate levels. One recent effort to incorporate this aspect into auction based procurement mechanisms has been due to Gallien and Wein[58].

The procurement scenario that they analyze is as follows (see Table 5 for notation): The buyer wants to procure q_j units of component $j \in \{1, \ldots, m\}$. There are n suppliers willing to supply some or all of these quantities subject to overall capacity constraints. Overall capacity constraints of resource (supplier) i is c_i and the usage can be described by a linear model where a_{ij} is the amount of resource i required for component j. An auctioneer acts as an intermediary between the buyer and the seller thereby decoupling the information between the two, much like what happens on `http://www.freemarkets.com/`.

1) The Auction Mechanism: The mechanism is designed as a multi round auction where in each round t the supplier i submits a bid $b_{ij}(t)$ to sell any quantity between 0 and q_j of component j. Further non-reneging and minimum bid decrement rules are in place. In each round of the auction a potential allocation $\mathbf{x}(t) = (x_{ij}(t))_{i \in \{1,\ldots,n\}, j \in \{1,\ldots,m\}}$ is obtained by solving the linear program given below.

$$\min \sum_{i=1}^{n} \sum_{j=1}^{m} b_{ij}(t) x_{ij}(t) \qquad (37)$$

$$s.t \qquad \sum_{j=1}^{m} a_{ij} x_{ij}(t) \leq c_i \quad \forall i; \qquad (38)$$

$$\sum_{i=1}^{n} x_{ij} = q_j \quad \forall j; \qquad (39)$$

$$x_{ij}(t) \geq 0 \quad \forall (i,j)$$

At the end of each round, the potential allocation $\mathbf{x}_i(t)$ is displayed to the supplier i which can be used to better the

bid in the following round. The supplier can choose to follow a *myopic best response (MBR)* strategy embedded within a software based bid suggestion device. To use this feature, the supplier i is required to submit his actual production costs v_{ij} for component j to the auctioneer. The next bid $\mathbf{b}_i^*(t+1)$ to be submitted by supplier i is such that he maximizes his potential payoff $\Pi_i(\mathbf{b}(t)) \equiv \sum_{j=i}^{m}(b_{ij}(t)-v_{ij})x_{ij}(t)$ in round t by carrying out the following computation:

$$\mathbf{b}_i^*(t+1) \equiv \sup\left[\arg \max_{0\leq \mathbf{w}\leq \mathbf{b}_i(t), \mathbf{w}\in(\epsilon N)^m} \Pi_i(\mathbf{w}, \mathbf{b}_{-i}(t))\right] \tag{40}$$

E. Summary and Current Art

In this section we reviewed mechanisms designed to support multi-item procurement scenarios. In the first part, we discussed a purely computational approach to the procurement decision problem to illustrate the computational problems that arise. In the next section we introduced economic concerns and discussed the limitations to achieving both computation and economic efficiencies. Finally we discussed the implications of capacity constraints at suppliers on decisions made through combinatorial auction models. Also, we deliberated on one approach to providing the suppliers with a bid suggestion device to help in reformulating bids in a complex combinatorial environment.

Currently, combinatorial auctions constitute a very active research area. There are several surveys that have appeared on this topic, for example, see [14], [15], [16], [17]. There is also a recent comprehensive book by Cramton, Shoham, and Steinberg [21]. There have been numerous efforts in solving the winner determination problems arising in complex combinatorial auctions. The reader is referred to the papers [39], [72], [73], [74], [75], [76], [77], [78], [52]. Another topic of active research is design of truthful combinatorial auctions. Please refer to [79], [80], [50] for more details. Design of iterative combinatorial auctions [17], [81], [82], [70] is one more direction in which a fair amount of research activity is in progress. Multi-attribute combinatorial auctions, however, have received little attention due to the intrinsic difficulties involved.

In the following section, we present real-world case studies of use of procurement auctions and discuss the implementation issues that arise.

VII. Case Studies of Electronic Procurement Mechanisms

Given the wide variety of procurement scenarios in practice and the emerging body of literature on procurement mechanisms reviewed this far, it is interesting to note the *feedback from the trenches*. Compaq Computer Corp, General Dynamics, Dutch Railway, General Electric, and Staples Inc. are some examples of companies that are pioneering users of auction technology for procurement [54], [3]. In this section, two cases that illustrate the successful translation of ideas in procurement auctions into practical business oriented implementations to provide a flavor of the emerging state of practice in procurement. The first of these cases illustrates the use of combinatorial and supply curve auctions by a leading global manufacturer of confectioneries - *MARS Incorporated* [6]. The second case describes the use of combinatorial auction methodology for procurement of logistics services by a very large retail chain - *Home Depot* [4], [5]. For another interesting case study, that of SEARS logistics, see [7].

A. Combinatorial and Supply Curve Auctions at MARS Inc.

Procurement at *MARS Inc* exhibits the following characteristics [6]: (1) the supply pool is small for each category of material sometimes by necessity and sometimes by design, (2) there is significant business integration, (3) single buyers are responsible for large portfolios of items, (4) contracts are executed with many types of suppliers including private businesses, traded agricultural markets, monopolies, cartels, and governments, (5) Negotiation and tendering are the most common procurement mechanisms, and (6) typical bids in these purchases include volume discounts and all-or-nothing bids.

MARS realized that the process could be inefficient for several reasons: (1) competitive positions cannot be fully leveraged for price negotiations, (2) synergies or complementarities in supply conditions cannot be fully exploited in item by item negotiation, (3) disproportionate amount of time is spent determining quantities and prices, and (4) lack of transparency in award of contracts because of arbitrariness in the negotiation process. Automated auctions, generally seen as mechanisms that promote market competition and that make negotiations efficient, were to be utilized to eliminate the limitations in the manual procurement process. However, auctions suffer from certain drawbacks too: firstly they are too reliant on price for market making, making them a brute force way of managing relationships and secondly they are inappropriate when the firm wants to control business volumes or the number of suppliers.

Volume discount and combinatorial auction models provide a natural way of capturing these and other business requirements such as minimizing the number of winning suppliers, limiting the exposure in business volume with a single supplier and truck load constraints, etc. Also, if two or more bid sets could win, then the buyer must choose the ones that arrived first so that the auction is seen as fair. Identifying the cost minimizing bid set subject to these rules is a NP-hard optimization problem. Approximate solutions to these hard problems are unacceptable since the difference between an approximate solution and an optimal one may result in completely different allocations, which runs counter to the fairness requirement of the procurement process.

1) The Auction Design: The Mars team working with researchers from the IBM T.J. Watson Research Center designed the auction mechanism that is currently used by buyers of MARS worldwide. In order to meet with the business requirements outlined earlier and to accommodate the complex bid structures, the team came up with an iterative auction design. An iterative auction design has certain advantages:

(1) it eliminates the need to completely specify the cost structure using bundled bids or volume discount bids which can result in exponentially large number of bids, (2) induces competition among suppliers as opposed to single shot bidding mechanisms, and (3) allows suppliers to correct their bids using information learned during the process.

Each iteration proceeds in two stages: the first involves collecting a set of bids and finding the set(s) that minimize the cost of procurement. This is used as an input to the second stage where another optimization problem is solved whose objective is to minimize the sum of time stamps of the submitted bids with an additional constraint being that the cost of procurement is equal to the minimum cost obtained in the first stage of the iteration. By adopting such a solution process both the requirements of *optimality* and *fairness* are met.

The winner determination problem for the combinatorial auction version, i.e. the problem of choosing the winning combination of bids from the set of submitted bids, is modeled as a set-covering problem with side constraints. For details of the modeling see [6]. Even without the inclusion of business rules, outlined earlier as side constraints, the problem is NP-hard. In order to solve this MIP formulation, a bid evaluation engine was developed as an independent module in C++ using IBM's OSL as the LP/IP solver. This engine has proven effective in solving problems with 500 items and up to 5000 bids.

In the case of the volume discount auction, the problem is modeled as a variation of the multiple choice knapsack problem. Using heuristics based on customized knapsack cover inequalities and column generation techniques, approximate solutions to within one percent of the optimal were obtained.

The supplier selection mechanism using the MIP framework was deployed using IBM's eCommerce platform - Websphere Commerce Suite 4.1 as part of MARS Inc's procurement website. The heuristics that were developed to solve the MIP formulations, that are known to be NP-hard, provided optimal solutions within two minutes response time. This was an important design criterion both from the standpoint of design of the mechanism to ensure optimality while maintaining the element of fairness, and the deployment of the solution. In order to ensure a steady rate of progress of the auction in practice, bids were collected every two minutes and an allocation decision was made. This decision was communicated back to the bidders to allow them to restructure their bids. So, the implementation criteria mandated that every time the MIP was solved, the maximum time available was two minutes.

2) Deployment Issues and Impact: In order to ensure a proper absorption of the technology into the organization and to make it a part of the procurement process, the team from MARS Inc took comprehensive steps. These included conducting training for buyers and suppliers on the use of the software, having held desk facilities in place during the conduct of an auction, and the grooming of key personnel to *champion* the use of the procurement mechanism. Buyers were also required to make adjustment to the content and scope of existing business processes. While previously, a large proportion of their time was spent negotiating prices and quantities, they were now required to desist from doing the same and leave this to the auction mechanism.

The impact of the auction mechanism on procurement processes at MARS Inc has been significant. The payback of the implementation was less than a year, mostly from better allocation of contracts. The intangibles too were many: first, the negotiation process has itself become efficient and transparent and has been vouched for by many of the participating suppliers; secondly, suppliers also felt that the auction mechanisms were *equitable* and *fair* allowing suppliers to present their unique selling propositions through the expressive bid processes. For more details on this case, the reader is referred to [6].

B. Combinatorial Auctions for Logistics Services at Home Depot

This case study is reported in [5], [4]. Home Depot (HD) is the world's largest home improvement retailer with over 1000 stores and 37 distribution centers in United States, Canada, Puerto Rico and Chile and growing aggressively. The stores act as both retail outlets as well as warehousing locations thereby combining economies of scale with a high level of customer service. Managing the logistics of this retailer involves coordinating over 7000 suppliers, numerous carriers, 1000 stores, and 37 distribution centers. A key component of this logistics effort is the transportation of over 40000 stock keeping units (SKU's) between entities in the supply chain using trucking companies. Traditionally, the bidding process for transportation contracts was completely manual wherein Home Depot would provide truckers with origin destination zip codes for each pair of locations within its network and the aggregate demand forecasts for the pair. Based on this sparse information, carriers would bid for each origin-destination pair that makes up a lane.

Such a bidding process has some obvious limitations: (1) carriers do not have good visibility to HD's network, (2) it did not allow carriers to bid on combinations of lanes to exploit potential synergies thereby limiting their ability to bid more aggressively on synergistic lanes, (3) the manual process is extremely inefficient. To achieve better efficiencies and effectiveness in transportation services, HD partnered with i2 Technologies, a leading provider of supply chain optimization software. A new flexible bidding mechanism deployed on the Internet was developed to allow carriers to bid for combinations of lanes as well as for individual lanes.

1) Design of the New Bidding Mechanism: The new bidding mechanism consists of three separate stages. The first is a pre-qualification stage where HD provides potential bidders with information on origin destination pairs, the lane details and the forecast demand by equipment type. In return, carriers are required to provide pre-qualification information. Based on this information HD eliminates some of the carriers. Qualified carriers are then asked to send in their bids for individual lanes and combinations. HD preferred a single shot sealed bid combinatorial auction in contrast to the iterative auction used by MARS Inc. This was done to prevent carriers from engaging in a damaging price war that was seen as potential long-term risk in the quality of service.

The second stage involves the selection of winning bids from among a list of pre-selected bids. HD eliminates some of bids that it considers are inferior to other bids that have been received. An integer programming formulation based upon the set partitioning problem is solved in order to identify the winning combination of bids. In this stage a subset of the lanes that were originally put out for auction were allocated. The remaining lanes were auctioned in the third stage of the bidding process.

In the third stage, HD used information from previously submitted bids to identify and invite a set of potential carriers who would be likely to submit "acceptable" bids for the unallocated lanes. The optimization engine was used again to award the remaining lanes based on the bids collected in the second round of bidding.

2) Bidding Software and Implementation Impact: The bidding software consisted of three main components: (1) Shipper bid support (SBS), (2) Carrier bid response (CBR) and (3) Bid selection optimization engine. The SBS module helps Home Depot to analyze their network and decide which lanes to put out for a bid. The CBR module helps carriers analyze the demand data provide by Home Depot and create bids that complement their cost structures and existing networks. The Bid selection engine is an optimization module that solves an underlying integer programming formulation of the auction problem.

The new bidding mechanism was quite a success, allowing Home Depot to realize better rates. The reactions of the carriers have also been positive because it has allowed them to express their cost structures better through the combinatorial bidding mechanism. For more details on this case, the reader is referred to [5], [4].

VIII. Conclusions and Future Work

In this paper, we have surveyed the state-of-the-art in auction-based schemes for automating negotiations in electronic procurement. We have discussed these mechanisms under three categories:

- Procurement of single unit or multiple units of a single item based on a single attribute
- Procurement of multiple units of a single item based on multiple attributes
- Procurement of single unit or multiple units of multiple items based on a single attribute (combinatorial procurement)

A fourth category would be: procurement of multiple units of multiple items based on multiple attributes. Since the first three categories are areas of active research with many unresolved issues, the fourth category would be even more challenging.

In each of the three categories of procurement, we discussed several representative procurement scenarios and provided problem formulations with a discussion of computational complexity of the supplier selection or the winner determination problem. We also briefly discussed two case studies (Mars Inc. and Home Depot) involving the deployment of some of the auctions in real-world procurement problems.

Currently, the area of procurement auctions is a very active research area with plenty of open problems. Here, we handpick the following problems as the most important ones to study:

Winner Determination Problem in Procurement Auctions

Though extensive work has been done on solving the winner determination problem in different types of procurement auctions, there is still wide scope for future work here. One of the promising directions is to come up with efficient approximation algorithms with provable bounds for solving the winner determination problem. There are many efforts in this direction already, see for example, [49], [51]. The rich body of literature available in combinatorial optimization and approximation and randomized algorithms will be extremely useful here.

Iterative Procurement Auctions

As already stated in the paper, iterative mechanisms have several advantages over one shot mechanisms. Also, there have been several iterative mechanisms developed for procurement [17], [70], [39], [82]. Iterative mechanisms are appealing to the buyer and suppliers because they enable the bidders to apply corrections to their bids in a continuous way. More work is required in ensuring that iterative mechanisms satisfy desirable economic properties also.

Design of Incentive Compatible Mechanisms

Inducing truth revelation will continue to be a major issue in the design of procurement mechanisms. Designing such mechanisms has intrinsic difficulties such as very high computational complexity and loss of efficiency. It would be interesting to study how the use of approximate algorithms for winner determination and payment computation would affect incentive compatibility. There is already a fair amount of work in this direction [51], [81], [50].

Multi-Attribute Procurement

Multi-attribute procurement is an intrinsically difficult problem, but at the same time an important problem that needs immediate attention. There are a few results available [53], [60] and there are a few promising approaches such as goal programming [62], but much more needs to be researched in this area.

Use of Learning in Procurement Auctions

Procurement auctions provide an ideal platform for use of machine learning techniques in improving the efficiency of the process. The history of bidding by a supplier is an important parameter for winner determination. To incorporate history into procurement decision making will call for use of appropriate machine learning techniques such as reinforcement learning. Learning based models would be useful in iterative procurement auctions to help the buyer estimate the cost functions of the suppliers and in optimally incrementing the procurement budgets. One such application is discussed in [83]. We believe machine learning techniques have powerful applications in procurement auctions.

Procurement Auctions from a Total Supply Chain Perspective

It is important to design procurement mechanisms based on a total cost approach where the total cost captures all aspects of the entire supply chain. This has been explored in a few papers already [22] but a deeper understanding and a more systematic approach is required here.

Deployment Issues

Practical deployment of procurement auctions will throw up numerous challenges. Several authors have addressed these issues: security of transactions [84]; collusion of suppliers [85]; user interface issues [59]; fairness issues [15]; failure freeness and robustness against failures [15], [84], [43]. These issues need immediate attention if for successful adoption of auctions by purchasing departments. Designing software implementation frameworks so as to allow sensitivity analysis of procurement decisions in complex supply chain environments is also an important issue. Use of multi-agent agent technology in automating standard electronic procurement problems is one more issue. Using emerging Internet technology standards such as ebXML in implementing e-procurement solutions is an immediate practical issue.

Procurement Exchanges

Procurement exchanges are those where there are multiple buyers and multiple suppliers and the exchange facilitates matching of buyers with suppliers. All the issues become more complex with exchanges because of the presence of multiple buyers. There is a large body of literature on exchanges; for example, see [86], [18].

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